IN THE UNITED STATES PATENT AND TRADEMARK OFFICE

Application : **09/627,139**

Applicant(s) : **Schaffer et al.**

Filed : **7/27/2000**

Confirmation : **1204**

T.C./Art Unit : **2611**

Examiner : **Huynh, Son P.**

Atty. Docket : **US-000179**

Title: **THREE-WAY MEDIA RECOMMENDATION METHOD AND SYSTEM**

Mail Stop: **APPEAL BRIEF - PATENTS**
Commissioner for Patents
Alexandria, VA 22313-1450

APPEAL UNDER 37 CFR 41.37

Sir:

This is an appeal from the decision of the Examiner dated 29 December 2005, finally rejecting claims 1-26 of the subject application.

This paper includes (each beginning on a separate sheet):

1. **Appeal Brief;**
2. **Claims Appendix;**
3. **Evidence Appendix; and**
4. **Related Proceedings Appendix.**

APPEAL BRIEF

I. REAL PARTY IN INTEREST

The above-identified application is assigned, in its entirety, to **Philips Electronics North America.**

II. RELATED APPEALS AND INTERFERENCES

Appellant is not aware of any co-pending appeal or interference that will directly affect, or be directly affected by, or have any bearing on, the Board's decision in the pending appeal.

III. STATUS OF CLAIMS

Claims 27-29 are canceled.

Claims 1-26 are pending in the application.

Claims1-6, 9-14, and 17-26 stand rejected by the Examiner under 35 U.S.C. 102(e).

Claims 7-8 and 15-16 stand rejected by the Examiner under 35 U.S.C. 103(a).

These rejected claims are the subject of this appeal.

IV. STATUS OF AMENDMENTS

No amendments were filed subsequent to the final rejection in the Office Action dated 29 December 2005.

V. SUMMARY OF CLAIMED SUBJECT MATTER

The invention includes methods and systems for providing recommendations based on at least two sets of predictions that are based on at least two sets of profile data.

Predictions of material that a user is likely to prefer are typically based on profile data derived from explicit and implicit user preferences. Explicit user preferences include, for example, a user's response to a questionnaire (page 19, lines 11-24; FIG. 7); implicit user preferences include, for example, determined preferences based on the user's viewing habits (page 17, line 22 – page 18, line 13; FIG. 6). Alternatively, a mix of preferences and viewing can be used, wherein a user explicitly ranks programs that the user has viewed (page 16, lines 1-12; FIG. 5).

As contrast to conventional techniques of generating a set of predictions based on a blend of explicit and implicit user feedback, this invention uses at least two profiles of a user's preferences to generate at least two sets of predictions (335 and 342 in FIG. 8), and weight-averages the predictions (335, 342), to form a composite set of predictions (340; detailed at page 21, lines 8-13). Each of the sets of predictions (335, 342) may be based on one of the user's profiles (315), or a combination of the user's profiles (325, 330). By generating two distinct sets of predictions (335, 342), the predictions formed from one or more sets of profiles can stand alone, or can be used to modify the predictions from other sets of profiles, based on the weights assigned to each set of predictions (page 10, lines 12-14). Additionally, rules can be defined for choosing one or the other set of predictions when the different profiles produce highly disparate predictions (page 21, lines 14-20). These advantages cannot be achieved by a system that creates and uses a single user profile to generate a single set of predictions.

Independent claim 1 recites an automated recommendation system, comprising:

a processor (240 of FIG. 4) connected to receive resource data (235 of FIG. 4) defining available resources and at least two sets of profile data (315, 325, 330 of FIG. 8 and page 20, line 17 – page 21, line 1), each defining a user's preferences with respect to the resources;

each of the sets of profile data being derived from a different class of interaction of the user with a first portion of the resource data and usable to predict a given resource's desirability based on each of the sets (FIGs. 5, 6, 7, and page 16, line 1-page 20, line 8);

the processor being adapted to:

generate (page 20, line 9 – page 21, line 1) at least two sets of predictions (335, 342 of FIG. 8) based on one (360 of FIG. 8) or a combination (370 of FIG. 8) of the sets of profile data (315, 325, 330 of FIG. 8), and

combine the predictions by weight-averaging corresponding ones from each of the at least two sets of predictions (page 21, lines 4-13).

Independent claim 9 recites a method of recommending resources, comprising:

generating (page 16, line 1-page 20, line 8) at least two sets of profile data (315, 325, 330 of FIG. 8) based on expressed preferences of a user with respect to the resources each being usable to predict a given resource's desirability based on each of the sets;

generating (page 20, line 9 – page 21, line 1) at least two sets of predictions (335, 342 of FIG. 8) based on one (315 of FIG. 8) or a combination (235+330, via 370 of FIG. 8) of the sets of profile data; and

combining the predictions by weight-averaging corresponding ones from each of the at least two sets of predictions (page 21, lines 4-13).

Independent claim 18 recites an automated recommendation system, comprising:

a processor (240 of FIG. 4) connected to receive resource data defining available resources (235 of FIG. 4) and sets of profile data (315, 325, 330 of FIG. 8), each defining a user's preferences with respect to the resources;

the sets of profile data including

a set of explicit profile data (315) indicating express indications by a user of preferred classes of programming rather than indications by the user of particular resources that are preferred;

a feedback data set (325) derived from ratings provided by the user with respect to a particular resource in the resource data; and

an implicit data set (330) derived from machine-observation of a user's resource use history, whereby the implicit data reflects the user's selection;

the processor being adapted to generate at least two sets of predictions (335, 342 of FIG. 8) based on one or a combination of the sets of profile data, each of the predictions including a confidence level (page 21, lines 4-8); and

the processor being further adapted to combine the predictions by weight-averaging corresponding ones from each of the at least two sets of predictions to produce a combined set (page 21, lines 8-13).

Independent claim 21 recites a method of automatically recommending resources, comprising:

receiving resource data defining available resources and sets of profile data (315, 325, 330 of FIG. 8), each defining user preferences with respect to the resources;

the sets of profile data including

a set of explicit profile data (315) indicating express indications by a user of preferred classes of programming rather than indications by the user of particular resources that are preferred;

a feedback data set (325) derived from ratings provided by the user with respect to a particular resource in the resource data; and

an implicit data set (330) derived from machine-observation of a user's resource use history, whereby the implicit data reflects the user's selection;

generating (page 20, line 9 – page 21, line 1) at least two sets of predictions (335, 342 of FIG. 8) based on one (315) or a combination of the sets (325+330, via 370 of FIG. 8) of profile data, each of the predictions including a confidence level (page 21, lines 4-8); and

combining (page 21, lines 8-13) the predictions by weight-averaging corresponding ones from each of the at least two sets to produce a combined set (340 of FIG. 8).

Independent claim 24 recites a method of combining profile data, comprising:

generating first profile data by receiving through a user interface user preferences in the form of expressed generalized preferences corresponding classes of resources (FIG. 7, page 7, lines 16-23);

generating second profile data by receiving user preferences in the form of rating data corresponding to specific resources (FIG. 5, page 7, line 24 – page 9, line 7); and

applying the first and second profile data to respective prediction engines to produce first and second prediction results (360, 365 of FIG. 8) and combining (375 of FIG. 8) the first and second results (375 of FIG. 8[1]).

[1] Note that although FIG. 8 is used as an example embodiment of the elements of the claims, the claims are not limited to this example. FIGs. 9 and 10 illustrate other example embodiments, and other embodiments would be evident to one of ordinary skill in the art in view of the disclosure of this invention.

VI. GROUNDS OF REJECTION TO BE REVIEWED ON APPEAL

Claims 1-6, 9-14, and 17-26 stand rejected under 35 U.S.C. 102(e) over Hosken (USP 6,438,579).

Claims 7-8 and 15-16 stand rejected under 35 U.S.C. 103(a) over Hosken and Bergh (USP 6,112,186).

VII. ARGUMENT

Claims 1-6, 9-14, and 17-26 stand rejected under 35 U.S.C. 102(e) over Hosken

MPEP 2131 states:

> "A claim is anticipated only if ***each and every element*** as set forth in the claim is found, either expressly or inherently described, in a single prior art reference." *Verdegaal Bros. v. Union Oil Co. of California*, 814 F.2d 628, 631, 2 USPQ2d 1051, 1053 (Fed. Cir. 1987). "The ***identical invention*** must be shown in as ***complete detail*** as is contained in the ... claim." *Richardson v. Suzuki Motor Co.*, 868 F.2d 1226, 1236, 9 USPQ2d 1913, 1920 (Fed. Cir. 1989).

Claims 1-6

Claim 1, upon which claims 2 and 6 depend, claims an automated recommendation system that includes a processor that receives at least two sets of profile data defining a user's preferences, each of the sets of profile data being derived from a different class of interaction of the user, generates at least two sets of predictions based on one or a combination of the sets of profile data, and combine the predictions by weight-averaging corresponding ones from each of the at least two sets of predictions.

Hosken fails to teach generating at least two sets of predictions based on two sets of profile data defining a user's preference, and Hosken fails to teach weight-averaging these at least two sets of predictions.

The Office action asserts that Hosken's implicit and explicit profile data input correspond to the claimed two sets of profile data. The applicants respectfully

disagree with this assertion. Hosken specifically teaches that the various sources of user feedback (implicit and explicit) are each used to update a user's profile 24:

> "the amount of time spent by a user apparently reviewing some biographical information about a particular media item, or the time spent listening to a music clip provides implicit information regarding the interest level of the user in a particular media content item. By extension, this implicit level of interest can also be used to imply a likely level of interest in other media content items with similar characterizing attributes. The implicit information gathered from user actions is preferably processed 22 and stored as an addition and refinement of the profile data 24 previously stored." (Hosken, column 5, lines 53-62.)

Hosken does not maintain different sets of user profile data based on the source of the feedback from the user. The applicants take particular note of Hosken's consistent use of the singular "profile" when referencing a user's profile:

> "A content and collaborative filtering system for recommending entertainment oriented content items, such as music and video, and other media content items to a user based on similarity in ***profile*** between the user and other users and between the content indexed in ***the user's profile*** and other content in the database. The system stores implicit and explicit ratings data for such content items provided by the users. Upon request of the user, the system accesses ***the user's profile*** and corresponding content interests database." (Hosken's Abstract.)
>
> "A history of the recommendation sets presented to a user may also be recorded in or stored in connection with ***the user profile***. Additionally, the level of interest in particular recommended media content items, particularly as can be inferred through the browsing of such recommendations in accordance with the present invention, is stored as part of ***the user profile***. Thus, the media content items considered or reviewed in connection with the user browsing actions are at least implicitly rated by the user and stored to ***the user profile***, which substantially extends and enhances both the individual and group-oriented basis for correlating user profiles." (Hosken, column 7, lines 37-48.)
>
> If the correlation meets the correlation threshold, indicating similar tastes, the system would compare the two user profiles, identifying any items contained in the user profile vector that were not present in ***the current user profile***. (Hosken, column 15, lines 61-64.)

There is not one instance in Hosken wherein Hosken references multiple profiles associated with a user. The only instances of the plural "profiles" occur when Hosken refers to the profiles of multiple users.

Because Hosken teaches a single profile per user, which profile includes refinements based on all of the classes of interaction (explicit, implicit) with the user, Hosken cannot create different sets of recommendations based on different sets of profiles corresponding to such classes of interaction. Because Hosken cannot create different sets of recommendations based on different sets of profile data defining a user's preferences, Hosken cannot weight-average such sets.

The Office action notes that Hosken teaches generating different sets of predictions, but fails to show that these different sets of predictions are based on different profiles derived from different classes of interaction of the user, as specifically claimed in claim 1. As taught by Hosken, "content recommendations" are generated based on the particular user's profile, and "collaborative recommendations" are generated based on the profiles of similar users and/or clusters of users (Hosken, column 14, line 40 – column 16, line 21). Hosken does not teach generating two sets of predictions based on two sets of profile data defining a user's preferences.

Because Hosken fails to teach generating at least two sets of predictions based on two sets of profile data defining a user's preference, and because Hosken fails to teach weight-averaging these at least two sets of predictions, as specifically claimed in claim 1, the applicants respectfully maintain that the rejection of claims 1-6 under 35 U.S.C. 102(e) over Hosken is unfounded, per MPEP 2131, and should be reversed by the Board.

Claims 9-14 and 17

Claim 9, upon which claims 10-17 depend, claims a method of recommending resources that includes generating at least two sets of profile data based on expressed preferences of a user with respect to the resources, each being usable to predict a given resource's desirability based on each of the sets, generating at least two sets of predictions based on one or a combination of the sets of profile data, and combining the predictions by weight-averaging corresponding ones from each of the at least two sets of predictions.

As detailed above, Hosken fails to teach generating at least two sets of profile data based on expressed preferences of a user, fails to teach generating at least two sets of predictions based on one or a combination of the sets of profile data, and fails to teach combining the predictions by weight-averaging corresponding ones from each of the at least two sets of predictions. Accordingly, the applicants respectfully maintain that the rejection of claims 9-14 under 35 U.S.C. 102(e) over Hosken is unfounded, per MPEP 2131, and should be reversed by the Board.

Claims 18-20

Claim 18, upon which claims 19 and 20 depend, claims an automated recommendation system, that includes sets of profile data associated with a user, including: a set of explicit profile data, a feedback data set, and an implicit data set; and a processor that generates at least two sets of predictions based on one or a combination of the sets of profile data, and combines the predictions by weight-averaging corresponding ones from each of the at least two sets of predictions.

As detailed above, Hosken fails to teach sets of profile data associated with a user, fails to teach generating at least two sets of predictions based on one or a combination of the sets of profile data, and fails to teach combining the predictions by weight-averaging corresponding ones from each of the at least two sets of predictions. Accordingly, the applicants respectfully maintain that the rejection of claims 18-20 under 35 U.S.C. 102(e) over Hosken is unfounded, per MPEP 2131, and should be reversed by the Board.

Claims 21-23

Claim 21, upon which claims 22 and 23 depend, claims a method that includes receiving sets of profile data, including a set of explicit profile data, a feedback data set, and an implicit data set; generating at least two sets of predictions based on one or a combination of the sets of profile data; and combining the predictions by weight-averaging corresponding ones from each of the at least two sets of predictions to produce a combined set.

As detailed above, Hosken fails to teach sets of profile data associated with a user, fails to teach generating at least two sets of predictions based on one or a combination of the sets of profile data, and fails to teach combining the predictions by weight-averaging corresponding ones from each of the at least two sets of predictions. Accordingly, the applicants respectfully maintain that the rejection of claims 21-23 under 35 U.S.C. 102(e) over Hosken is unfounded, per MPEP 2131, and should be reversed by the Board.

Claims 24-26

Claim 24 claims a method of combining profile data, that includes generating first and second profile data by correspondingly receiving user preferences in different forms and applying the first and second profile data to respective prediction engines to produce first and second prediction results and combining the first and second results.

As detailed above, Hosken fails to teach generating multiple sets of profile data corresponding to the different forms of receiving a user's preferences, fails to teach applying these multiple profile data to generate multiple prediction results, and fails to teach combining such multiple prediction results. Accordingly, the applicants respectfully maintain that the rejection of claims 24-26 under 35 U.S.C. 102(e) over Hosken is unfounded, per MPEP 2131, and should be reversed by the Board.

Claims 7-8 and 15-16 stand rejected under
35 U.S.C. 103a over Hosken and Bergh

MPEP 2142 states:

> "To establish a *prima facie* case of obviousness … the prior art reference (or references when combined) ***must teach or suggest all the claim limitations***… If the examiner does not produce a *prima facie* case, the applicant is under no obligation to submit evidence of nonobviousness."

Claims 7-8

Claims 7 and 8 are dependent upon claim 1. In this rejection, the Office action relies on Hosken for teaching the elements of claim 1.

As noted above, Hosken fails to teach each of the limitations of claim 1. The applicants respectfully maintain that the rejection of claims 7-8 under 35 U.S.C. 103(a) that relies on Hosken for teaching the elements of claim 1 is unfounded, per MPEP 2142, and should be reversed by the Board.

Claims 15-16

Claims 15 and 16 are dependent upon claim 9. In this rejection, the Office action relies on Hosken for teaching the elements of claim 9.

As noted above, Hosken fails to teach each of the limitations of claim 9. The applicants respectfully maintain that the rejection of claims 15-16 under 35 U.S.C. 103(a) that relies on Hosken for teaching the elements of claim 9 is unfounded, per MPEP 2142, and should be reversed by the Board.

CONCLUSIONS

Because Hosken fails to teach generating at least two sets of predictions based on two sets of profile data defining a user's preference, and because Hosken fails to teach weight-averaging these at least two sets of predictions, the applicants respectfully request that the Examiner's rejection of claims 1-6, 9-14, and 17-26 under 35 U.S.C. 102(e) and claims 7-8 and 15-16 under 35 U.S.C. 103(a) be reversed by the Board, and the claims be allowed to pass to issue.

Respectfully submitted

/Robert M. McDermott/
Robert M. McDermott, Esq.
Registration Number 41,508
804-493-0707

Please direct all correspondence to:
Yan Glickberg, Esq.
Philips Intellectual Property and Standards
P.O. Box 3001
Briarcliff Manor, NY 10510-8001
914-333-9618

CLAIMS APPENDIX

1. An automated recommendation system, comprising

a processor connected to receive resource data defining available resources and at least two sets of profile data, each defining a user's preferences with respect to the resources;

each of the sets of profile data being derived from a different class of interaction of the user with a first portion of the resource data and usable to predict a given resource's desirability based on each of the sets;

the processor being adapted to:

generate at least two sets of predictions based on one or a combination of the sets of profile data, and

combine the predictions by weight-averaging corresponding ones from each of the at least two sets of predictions.

2. A system as in claim 1, wherein the processor is further adapted to:

generate a weighted sum of corresponding records from each of the sets of profile data to generate a single combined set of profile data, and

generate at least one of the sets of predictions from the single combined set.

3. A system as in claim 2, wherein the processor is connected to control a delivery of resources corresponding to the resource data and responsively to the predictions.

4. A system as in claim 1, wherein the processor is connected to control a delivery of resources corresponding to the resource data and responsively to the predictions.

5. A system as in claim 1, wherein the at least two profile data sets include a feedback data set derived from ratings provided by the user with respect to a particular resource in the resource data.

6. A system as in claim 1, wherein the at least two profile data sets include an implicit data set derived from machine-observation of a user's resource use history, whereby the implicit data reflects the user's selections of resources to use.

7. A system as in claim 1, wherein at least one set of the at least two profile data sets comprises input vectors, and the input vectors each include feature-value pairs.

8. A system as in claim 1, wherein at least one set of the at least two profile data sets comprises input vectors, and the input vectors include feature-value pairs and a rating value.

9. A method of recommending resources, comprising:

generating at least two sets of profile data based on expressed preferences of a user with respect to the resources, each being usable to predict a given resource's desirability based on each of the sets;

generating at least two sets of predictions based on one or a combination of the sets of profile data; and

combining the predictions by weight-averaging corresponding ones from each of the at least two sets of predictions.

10. A method as in claim 9, further comprising:

generating a weighted sum of corresponding records from each of the sets of profile data to generate a single combined set of profile data; and

generating at least one of the sets of predictions from the single combined set.

11. A method as in claim 10, further comprising controlling a delivery of resources corresponding to the resource data responsively to the predictions.

12. A method as in claim 9, further comprising controlling a delivery of resources corresponding to the resource data responsively to the predictions.

13. A method as in claim 9, wherein generating the at least two sets of profile data includes generating a feedback data set by accepting ratings from the user with respect to a particular resource in the resource data.

14. A method as in claim 9, wherein generating the at least two sets of profile data includes generating an implicit data set by observing the user's resource use history, whereby the implicit data reflects the user's selections of resources to use.

15. A method as in claim 9, wherein at least one set of the at least two sets of profile data comprises input vectors, and the input vectors each include feature-value pairs.

16. A method as in claim 9, wherein at least one set of the at least two sets of profile data comprises input vectors, and generating the at least two sets of profile data includes generating feature-value pairs and a rating value.

17. A method as in claim 9, wherein: the sets of profile data includes:

a set of explicit profile data indicating express indications by a user of preferred classes of programming rather than indications by the user of particular resources that are preferred;

a feedback data set derived from ratings provided by the user with respect to a particular resource in the resource data; and

an implicit data set derived from machine-observation of a user's resource use history, whereby the implicit data reflects the user's selection.

18. An automated recommendation system, comprising

a processor connected to receive resource data defining available resources and sets of profile data, each defining a user's preferences with respect to the resources;

the sets of profile data including:

a set of explicit profile data indicating express indications by a user of preferred classes of programming rather than indications by the user of particular resources that are preferred;

feedback data set derived from ratings provided by the user with respect to a particular resource in the resource data; and

an implicit data set derived from machine-observation of a user's resource use history, whereby the implicit data reflects the user's selection;

the processor being adapted to generate at least two sets of predictions based on one or a combination of the sets of profile data, each of the predictions including a confidence level;

the processor being further adapted to combine the predictions by weight-averaging corresponding ones from each of the at least two sets of predictions.

19. A system as in claim 18, wherein the processor is further adapted to adjust weights of the weight averaging responsively to a difference between the corresponding ones.

20. A system as in claim 18, wherein the processor is further adapted to selectively override the weight averaging responsively to a difference between the corresponding ones.

21. A method of automatically recommending resources, comprising

receiving resource data defining available resources and sets of profile data, each defining user preferences with respect to the resources; the sets of profile data including:

a set of explicit profile data indicating express indications by a user of preferred classes of programming rather than indications by the user of particular resources that are preferred;

a feedback data set derived from ratings provided by the user with respect to a particular resource in the resource data; and

an implicit data set derived from machine-observation of a user's resource use history, whereby the implicit data reflects the user's selection;

generating at least two sets of predictions based on one or a combination of the sets of profile data, each of the predictions including a confidence level; and

combining the predictions by weight-averaging corresponding ones from each of the at least two sets of predictions to produce a combined set.

22. A method in claim 21, wherein combining the predictions includes adjusting weights of the weight averaging responsively to a difference between the corresponding ones.

23. A method as in claim 21, wherein combining the predictions includes selectively overriding the weight averaging responsively to a difference between the corresponding ones such that a prediction of a one of the sets of predictions is included in the combined set and a prediction of the other of the sets of predictions is excluded.

24. A method of combining profile data, comprising:

generating first profile data by receiving through a user interface user preferences in the form of expressed generalized preferences corresponding classes of resources;

generating second profile data by receiving user preferences in the form of rating data corresponding to specific resources; and

applying the first and second profile data to respective prediction engines to produce first and second prediction results and combining the first and second results.

25. A method as in claim 24, further including combining the first and second profile data, wherein combining the first and second profiles includes weight averaging corresponding ones of the profile data.

26. A method as in claim 24, wherein combining respective results includes selectively weight averaging corresponding ones of the predictions.

EVIDENCE APPENDIX

No evidence has been submitted that is relied upon by the appellant in this appeal.

RELATED PROCEEDINGS APPENDIX

Appellant is not aware of any co-pending appeal or interference which will directly affect or be directly affected by or have any bearing on the Board's decision in the pending appeal.